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PHYSICS-DATA MODELING FOR ENHANCED PERFORMANCE OF AUTOMATED CONSTRUCTION SYSTEM

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Abstract
Ensuring both operational efficiency and structural safety in Automated Construction Systems (ACS) remains a critical challenge, particularly under complex high-rise construction environments characterized by uncertain loads and limited sensing precision. To address this issue, this study develops a hybrid physics–data-driven modeling framework to improve jacking efficiency and structural reliability of ACS under such complex conditions. The framework integrates a Physics-Informed Neural Network (PINN) for predicting hydraulic cylinder strokes with a Generative Adversarial Network (GAN)-based anomaly detection model for structural safety evaluation. These models are embedded within a multi-objective optimization strategy, which is solved using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and further refined through the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Validation using real-world ACS monitoring data demonstrates that the proposed framework can significantly enhance jacking efficiency while maintaining structural safety within acceptable thresholds. The findings underscore the potential of combining physical modeling, machine learning, and evolutionary optimization to enable intelligent control of complex construction machinery.

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Keywords: Automated construction system, efficiency, structural safety, physics-informed neural network, multi-objective optimization.

1. Introduction

In the modern construction industry, the Automated Construction System (ACS) has emerged as a preferred form of construction machinery, providing a more controlled and efficient environment for high-rise building projects. Despite its advantages, the structural stability of ACS during operation remains highly vulnerable to dynamic disturbances, such as variable loads and strong wind forces at elevated working heights. These uncertainties pose significant challenges to achieving reliable attitude control in ACS operations.

First, the system's safety is difficult to guarantee under dynamic loading and environmental disturbances, especially when multiple jacking points must remain synchronized. Second, the efficiency of lifting operations is often compromised due to conservative control mechanisms. Third, current attitude control approaches typically rely on manually tuned Proportional–Integral–Derivative (PID) parameters, which depend heavily on expert experience and on-site adjustments. This reliance not only introduces subjectivity but also limits adaptability to varying working conditions. Together, these issues significantly hinder the robustness and intelligence of ACS control in complex construction scenarios.

To overcome the limitations of traditional control strategies, data-driven methods have been increasingly proposed. Machine learning models, such as Artificial Neural Networks (ANN) [1], Support Vector Machine (SVM) [2], Random Forest (RF) [3], and Deep Neural Network (DNN) [4], have shown potential for capturing complex nonlinear dynamics. Nonetheless, purely data-driven models face critical

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challenges, including poor generalization under noisy conditions, a strong reliance on large training datasets, and a lack of interpretability, all of which restrict their applicability in safety-critical engineering problems.

This study proposes a hybrid framework that targets two key objectives: (1) the development of a Physics-Informed Neural Network (PINN) that embeds the governing physical laws of the self-climbing system into the learning process, thereby enabling accurate prediction of hydraulic cylinder strokes even under conditions of limited and noisy data; and (2) the integration of a Generative Adversarial Network (GAN)-based anomaly detection model with the PINN-based stroke prediction model to form dual fitness functions within a multi-objective optimization framework. The optimization process is conducted using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), with the aim of improving jacking efficiency and structural safety.

2. Literature review

2.1. Physics-data hybrid modeling in construction machinery operations

Machine learning techniques have been extensively applied to construction machinery [5]. However, purely data-driven methods exhibit inherent limitations, particularly their excessive dependence on the quantity and quality of training data. This leads to unsatisfactory predictive performance particularly when training datasets are limited or contaminated by noise. Moreover, purely data-driven surrogate models are treated as "black boxes", offering limited interpretability of their prediction outcomes.

To enhance both the generalizability and interpretability of machine learning models, physics-data hybrid modeling approaches become increasingly popular [6]. By incorporating domain-specific physical laws into neural network architectures, these models effectively constrain the learning process, thereby improving both predictive accuracy and model interpretability [7]. For example, Zhang et al. [8] proposed a physics-informed deep learning (PIDL) model that integrates the nonlinear dynamic characteristics of a tunnel boring machine's (TBM) hydraulic propulsion system into a deep neural network. Zhou et al. [9] embedded Euler–Lagrange dynamics into a multilayer perceptron (MLP) to predict load sway in mobile cranes, and Shen et al. [10] combined rigid-body dynamics with Gaussian Process Regression to achieve robust external force estimation for excavators. These studies demonstrate that embedding physical constraints can substantially enhance the reliability and interpretability of predictive models, especially under sparse or uncertain data conditions.

Despite the demonstrated success of PINNs in various applications, their application to ACS remains largely unexplored. This study seeks to address this gap by developing a PINN-based framework for accurately predicting hydraulic cylinder strokes during ACS operations.

2.2. Multi-objective optimization in construction machinery operations

Multi-objective optimization (MOO) plays a critical role in construction machinery operations, where conflicting objectives such as efficiency and safety must be simultaneously addressed. In recent studies, evolutionary algorithms such as Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Non-dominated Sorting Genetic Algorithm (NSGA-III) have been used to identify Pareto-optimal solutions across diverse scenarios [11]. NSGA-II is particularly effective for problems involving two or three objectives, utilizing a crowding-distance-based strategy to maintain solution diversity, while NSGA-III extends this approach by incorporating a reference-point-based mechanism, making it more suitable for problems with over three objectives. For example, Fu et al. [12] applied NSGA-II for real-time attitude control of TBMs, aiming to minimize both horizontal and vertical trajectory deviations through optimal thrust distribution among hydraulic cylinders. Wang et al. [13] employed NSGA-III to solve the multi-objective scheduling problem of overlapping tower cranes, aiming to minimize total energy consumption and the imbalance of energy usage among cranes. Similarly, Liu et al. [14] applied NSGA-III to optimize the scheduling of automated construction equipment, including excavators, graders, and compactors, by jointly considering processing time, total equipment load, and total energy consumption. However, most ACS-related studies apply multi-objective algorithms without incorporating physical constraints or safety indicators. And few works integrate predictive models directly into the optimization process. This separation between prediction and decision-making limits the system’s ability to adapt in real-time.

To overcome these limitations, this study introduces a dual-objective optimization strategy that incorporates the PINN-based stroke prediction model and the GAN-based safety evaluation model as fitness functions. NSGA-II is employed to generate a set of Pareto-optimal ACS operating parameters. These solutions are then ranked using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to identify the most balanced solution in terms of jacking efficiency and structural safety of the ACS.

3. Research approach

3.1. Physics-informed model structure for cylinder stroke prediction

3.1.1. Physical law for hydraulic cylinder stroke estimation

During the jacking process of the ACS, the vertical axis is subjected to complex coupled forces, including the thrust generated by hydraulic cylinders, static and dynamic loads from construction equipment, and material storage on the top platform, dynamic loads induced by personnel operating within suspended scaffolding, frictional resistance between the scaffold and the main structure during ACS self-climbing, and lateral wind forces from high-altitude environments. Following the approach proposed in [8], the force balance relationship for a single hydraulic cylinder can be expressed in a simplified form as:

$$m\frac{d^2(y_t-y_{t-u})}{dt^2}+c\frac{d(y_t-y_{t-u})}{dt}+k(y_t-y_{t-u})=A(P_t^1-P_t^2)-F_t \tag{1}$$

Where m is equivalent mass of the ACS, c is the damping coefficient, k is the stiffness coefficient, y_t *and* y_{u-t} are hydraulic cylinder strokes at the moments t and $t\text{-}u$, A is the effective area of the cylinder piston, P_t^1 and P_t^2 are the pressures at the oil inlet and the oil outlet of the hydraulic chamber, and F_t is external load. Generally, P_t^2 is negligible due to the low pressure inside the hydraulic chamber and we denote $P_t^1-P_t^2=P_t^1$.

To model the stroke difference between two hydraulic cylinders i and j, the individual force equilibrium equations are combined:

$$\begin{aligned}&m_i\frac{d^2(y_t^i-y_{t-u}^i)}{dt^2}-m_j\frac{d^2(y_t^j-y_{t-u}^j)}{dt^2}+c_i\frac{d(y_t^i-y_{t-u}^i)}{dt}-c_j\frac{d(y_t^j-y_{t-u}^j)}{dt}\\&+k_i(y_t^i-y_{t-u}^i)-k_j(y_t^j-y_{t-u}^j)=A_iP_t^i-A_jP_t^j-F_t^i+F_t^j\end{aligned} \tag{2}$$

Where P_t^i and P_t^j represent the inlet pressures of the i-th and j-th jacking hydraulic cylinders, respectively.

Assuming identical cylinders (i.e., $m_i=m_j=\overline{m}$, $A_i=A_j=\overline{A}$) and neglecting internal spring stiffness (since hydraulic cylinders typically do not have mechanical springs), the simplified dynamic model becomes:

$$\begin{aligned}&\overline{m}\frac{d^2(y_t^i-y_{t-u}^i-y_t^j+y_{t-u}^j)}{dt^2}+c_i\frac{d(y_t^i-y_{t-u}^i)}{dt}-c_j\frac{d(y_t^j-y_{t-u}^j)}{dt}\\&=\overline{A}(P_t^i-P_t^j)-F_t^i+F_t^j\end{aligned} \tag{3}$$

In theory, stroke estimation and control of the ACS can be achieved by solving this dynamic equation. However, in real-world high-rise construction environments, parameters such as c_i and c_j are often unknown or difficult to measure accurately. Therefore, PINN is adopted to incorporate the physical laws directly into the learning process, enabling robust predictions with limited or noisy field data.

3.1.2. Physics-informed neural network for cylinder stroke prediction

The proposed framework combines the flexibility of deep learning with embedded physical knowledge. The network is designed to map measured input features to predicted cylinder strokes:

$$X_t = [t, P_t^i, P_t^j, y_{t-u}^i, y_{t-u}^j, F_t^i, F_t^j] \tag{4}$$

The network outputs are:

$$Y = [\hat{y}_t^i, \hat{y}_t^j] \tag{5}$$

Where $\hat{y}_t^i$ and $\hat{y}_t^j$ are the predicted strokes of i-th and j-th jacking hydraulic cylinders at timestamp t.

The PINN model, denoted as $f_{PINN}(X_t;\theta)$, is constructed as a fully connected deep neural network with multiple hidden layers and ReLU activation functions. The loss function combines a supervised data loss and a physics-informed residual loss:

$$L_{\text{total}}(\theta) = L_{\text{data}}(\theta) + L_{\text{physics}}(\theta) \tag{6}$$

Where:

$$L_{\text{data}}(\theta) = \frac{1}{N}\sum_{t=1}^{N}[(\hat{y}_t^i - y_t^i)^2 + (\hat{y}_t^j - y_t^j)^2] \tag{7}$$

And

$$L_{\text{physics}}(\theta) = \frac{1}{N}\sum_{t=1}^{N}[R_t(\theta)^2] \tag{8}$$

Where:

$$\begin{aligned} R_t(\theta) = \bar{m}\frac{d^2(\hat{y}_t^i - y_{t-u}^i - \hat{y}_t^j + y_{t-u}^j)}{dt^2} + c_i\frac{d(\hat{y}_t^i - y_{t-u}^i)}{dt} \\ -c_j\frac{d(\hat{y}_t^j - y_{t-u}^j)}{dt} - \bar{A}(P_t^i - P_t^j) + F_t^i - F_t^j \end{aligned} \tag{9}$$

By embedding physical laws into the training process, the PINN model can achieve better generalization, improved interpretability, and enhanced robustness against noisy data.

3.2. GAN-based safety evaluation model for ACS

To assess the structural safety status of the ACS, a GAN-based anomaly detection framework is developed, particularly suited for scenarios where labeled anomaly data are scarce. Multivariate time-series data collected from strain gauges, inclinometers, leveling instruments, and hydraulic pressure sensors are utilized as input. First, the raw time-series data at timestamp t are organized into a feature vector:

$$Z_t = [S_t^1, S_t^2 \ldots, S_t^i, \ldots, S_t^n, P_t^1, P_t^2, \ldots, P_t^i \ldots, P_t^m] \tag{10}$$

Where S_t^i denotes the time-series data from i-th safety monitoring sensor at timestamp t; P_t^i represents the oil inlet pressure of the i-th jacking hydraulic cylinder at the moment t.

These signals are then transformed into multi-channel signature matrices H_t through a sliding-window-based cross-correlation process [15]:

$$H_t^{ij} = \frac{1}{w}\sum_{d=0}^{w-1} Z_{t-d}^{i} Z_{t-d}^{j} \tag{11}$$

Where w denotes the size of sliding windows.

Subsequently, a Deep Convolutional GAN (DCGAN) is trained, where the Generator (G) attempts to synthesize realistic signature matrices from random latent vectors, while the Discriminator (D) distinguishes between real and generated samples [16]. The adversarial training objective follows:

$$\min_G \max_D V(G, D) = E_{Z_t \sim p_{data}(Z_t)}[\log D(Z_t)] + E_{u \sim p_u(u)}[\log(1 - D(G(u)))] \tag{12}$$

Where $p_{data}(Z_t)$ is the distribution of real data, and $p_u(u)$ is the distribution of the random latent space.

After training, the discriminator is used to compute an anomaly score for each input matrix:

$$A(H_t^{ij}) = 1 - D(H_t^{ij}) \tag{13}$$

Finally, following the approach proposed in [17], a confusion-matrix-based threshold T is determined to minimize the classification error. Samples with anomaly scores exceeding T are classified as structural anomalies.

3.3. Multi-objective optimization for ACS performance

To simultaneously optimize ACS jacking efficiency and structural safety, a multi-objective optimization model is formulated. Specifically, the model targets two objectives: (1) maximizing predicted cylinder strokes, and (2) minimizing ACS anomaly scores. The optimization problem is formally expressed as:

$$\begin{aligned} &\max\{ f_{PINN}(X_t;\theta), -A(H_t^{ij}) \} \\ &s.t. \begin{cases} 100 \le P_t^i \le 350 \\ 100 \le P_t^j \le 350 \\ \hat{y}_t^i - \hat{y}_t^j \le \varepsilon \\ A(H_t^{ij}) \le T \end{cases} \end{aligned} \tag{14}$$

Where ε is the threshold of stroke difference between hydraulic cylinders, ensuring simultaneous jacking of hydraulic cylinders. The hydraulic cylinder operates within a normal pressure range of 100 to 350 bar under standard working conditions.

To solve the formulated multi-objective optimization problem, NSGA-II is employed to identify Pareto-optimal solutions by applying a fast non-dominated sorting process to rank individuals based on Pareto dominance. To maintain diversity among solutions, it introduces a crowding distance metric that encourages a well-distributed Pareto front [18]. Through iterative processes of selection, crossover, and mutation, NSGA-II evolves the population toward an optimal trade-off between conflicting objectives. Following the generation of the Pareto front, TOPSIS is applied to select the most balanced solution. TOPSIS evaluates each Pareto-optimal candidate by calculating its distance from an ideal solution (best possible performance) and a negative-ideal solution (worst possible performance) [19]. The solution with the closest proximity to the ideal point and the farthest distance from the negative-ideal point is selected as the optimal operating parameter set.

4. Case study

4.1. Case description

To validate the effectiveness of the proposed framework, a case study was conducted on a high-rise building construction project in Shenzhen, China. Located in a coastal urban area, the project faces substantial safety challenges due to strong prevailing winds and complex surrounding conditions during construction. Given the critical need to balance operational efficiency and structural stability, this project provides an ideal testbed for evaluating the performance of the proposed framework.

As part of the ACS deployed for this project, a total of 39 sensors were installed to monitor key mechanical and structural parameters. These sensors were strategically distributed across the eight main ACS supporting structures to enable comprehensive tracking of horizontal displacements, internal stresses, platform inclinations, hydraulic pressures, and cylinder strokes. The sensor network was configured to record measurements at 10-second intervals, resulting in a dataset comprising 48,210 time-series samples collected between November 17 and November 23, 2023. This dataset was subsequently used for model training, validation, and multi-objective optimization experiments.

4.2. Experiment setup

All data preprocessing, model training, and optimization experiments were conducted on a high-performance computing platform with an Intel Core™ i9-11900K @ 3.50GHz CPU, an NVIDIA GeForce RTX 3080 GPU, and 128G of RAM.

For cylinder stroke prediction, the PINN model was constructed with four hidden layers, configured with 64, 64, 32, and 32 neurons respectively, and using ReLU activation functions throughout. For structural safety evaluation, the generator consists of two fully connected layers followed by two fractionally-strided convolutional layers, with a Tanh activation function applied to the output layer. The discriminator comprises two convolutional layers, followed by a flattening layer and two fully connected layers, terminating in a Sigmoid activation function that outputs a probability score. All intermediate layers use Tanh activation functions. Both the generator and discriminator are trained using stochastic gradient descent (SGD) with a fixed learning rate of 0.001.

5. Results and discussion

5.1. Cylinder stroke prediction and safety evaluation

The predictive performance of the PINN-based cylinder stroke model was evaluated using the collected dataset, which was partitioned into training and testing subsets at a ratio of 8:2. Through model training and evaluation, the proposed model achieved a coefficient of determination (R^2) of 92.11% on the training set comprising 38,568 samples, and 88.73% on the test set with 9,642 samples, demonstrating strong predictive capability and generalization performance. As shown in the Fig.1(a), the horizontal and vertical axes represent the prediction deviations of two selected hydraulic cylinders (y_1 and y_2), respectively, with the color gradient indicating the density of data points—warmer colors denote higher density regions. Most prediction deviations are concentrated within approximately 1 mm, and nearly all deviations fall below 3.5 mm. Given that the average jacking displacement over a 10-second interval is approximately 12 mm, the prediction error is sufficiently small for practical applications. These results confirm that the PINN model effectively captures the dynamic behavior of the ACS and provides accurate stroke predictions.

The structural safety evaluation results generated by the GAN-based anomaly detection model are presented in Fig. 1(b). After being trained on data from normal operating conditions, the model outputs anomaly scores for each time step. A threshold of 0.6, optimized via confusion matrix analysis, is used to distinguish between normal and abnormal states. Data points with anomaly scores exceeding this threshold are identified as structural anomalies. The model successfully detects three distinct periods of abnormal behavior, as highlighted in the figure. These detected intervals closely align with manually labeled anomaly events, confirming the reliability of the GAN-based safety evaluation model. Furthermore, the anomaly scores exhibit temporal continuity, rather than sporadic outliers, suggesting that structural instability tends to persist over time once initiated—a phenomenon critical for intervention planning.

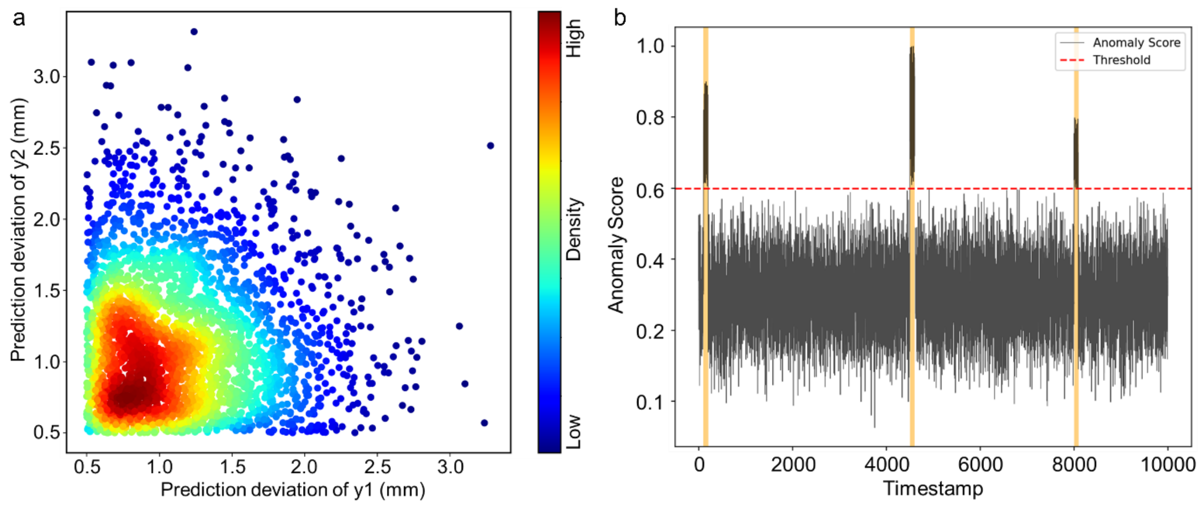

Fig. 1. (a) prediction deviation of cylinder strokes; (b) ACS anomaly detection over time.

5.2. Optimization of ACS performance

The trained PINN and GAN models were integrated into the multi-objective optimization framework to simultaneously enhance jacking efficiency and structural safety. The optimization problem was solved using the NSGA-II algorithm to generate a Pareto-optimal set of solutions, followed by TOPSIS-based ranking to select the most balanced operating parameters.

A set of 100 samples was selected to represent a continuous time segment that includes anomaly occurrences. Fig. 2(a) and Fig. 2(b) present the variations in hydraulic pressure parameters $P1$ and $P2$ before and after optimization. It can be observed that the latter half of the samples experienced significant adjustments, with most optimized cylinder pressures showing an upward trend relative to their original values. This reflects the model's adjustment strategy to enhance cylinder actuation forces for improving jacking efficiency.

Fig. 2(c) shows the improvement in average cylinder strokes (Avg_y) after optimization. On average, the stroke per 10-second interval increased by approximately 1.5 mm, indicating a notable enhancement in jacking efficiency without compromising system stability. The gradual increase in anomaly scores with sample index observed in Fig. 2(d) reflects the accumulation of subtle structural instabilities during the jacking process. As system parameters deviate from optimal values, the GAN-based discriminator captures this shift through rising anomaly scores. After optimization, all anomaly scores were effectively reduced below the threshold, with most stabilized around 0.45. This outcome demonstrates that the optimization not only improves jacking efficiency but also maintains structural safety within acceptable limits.

In summary, the experimental results validate the proposed framework. By combining physics-informed learning, GAN-based safety evaluation, and evolutionary optimization, the ACS achieves improved performance, even under uncertain working conditions.

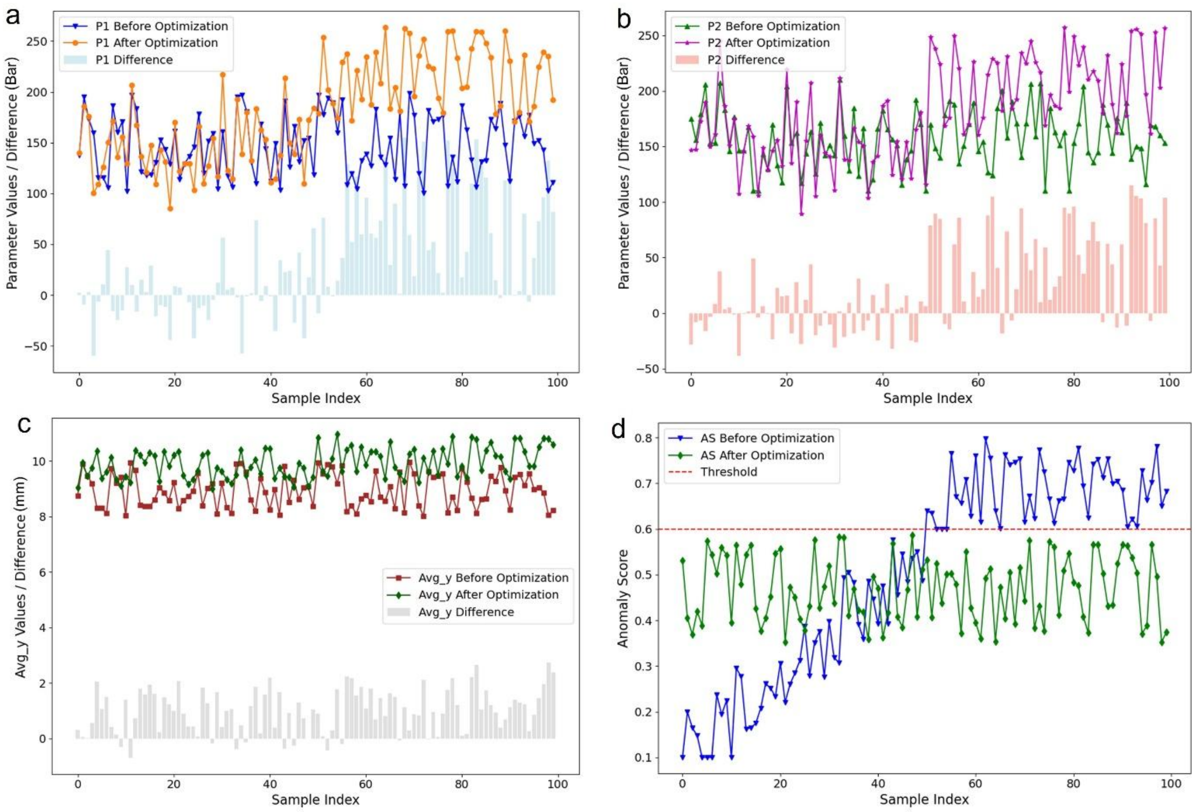

Fig. 2. (a) optimized ACS parameter values in P1; (b) optimized ACS parameter values in P2; (c) improvement in average cylinder strokes; (d) reduction in anomaly scores of ACS structure.

6. Conclusion

This study proposed a hybrid physics–data-driven modeling framework to enhance the performance of ACS in high-rise building construction. By integrating a PINN for cylinder stroke prediction, a GAN-based model for structural safety evaluation, and an NSGA-II-TOPSIS-based optimization strategy, the proposed framework simultaneously improves jacking efficiency and maintains structural stability. Validation using real-world project data demonstrated that the framework can effectively predict hydraulic behavior, detect potential structural anomalies, and optimize operating parameters to achieve balanced performance. Future research will focus on extending the framework to enable real-time adaptive control and on incorporating more complex environmental disturbances, such as varying wind loads and platform deformations, to further enhance its robustness and applicability.

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